SENSITIVITY ANALYSIS OF APEX FOR NATIONAL ASSESSMENT

X. Wang, S. R. Potter, J. R. Williams, J. D. Atwood, T. Pitts

ABSTRACT. *Sensitivity analysis for mathematical simulation models is helpful in identifying influential parameters for model outputs. Representative sets of APEX (Agricultural Policy/Environmental eXtender) model data from across the U.S. were used for sensitivity analysis to identify influential parameters for APEX outputs of crop grain yields, runoff/water yield, water and wind erosion, nutrient loss, and soil carbon change for a national assessment project: the Conservation Effects Assessment Project (CEAP). The analysis was based on global sensitivity analysis techniques. A test case, randomly selected from the representative sets of APEX model data, was first analyzed using both the variance−based sensitivity analysis technique and the enhanced Morris method. The analysis confirmed the reliability of the enhanced Morris measure in screening subsets of influential and non−influential parameters. Therefore, the enhanced Morris method was used for the national assessment, where the cost of applying variance−based techniques would be excessive. Although sensitivities are dynamic in both temporal and spatial dimensions, the very influential parameters (ranking 1st and 2nd) appear very influential in most cases. Statistical analyses identified that the NRCS curve number index coefficient is very influential for runoff and water−related output variables, such as soil loss by water, N and P losses in runoff. The Hargreaves PET equation exponent, moisture fraction required for seed germination, RUSLE C factor coefficient, and the potential heat units are influential for more than two APEX outputs studied. .*

Keywords. *APEX model, Enhanced Morris method, Sensitivity analysis, Variance−based method.*

Conservation programs help establish sustainable production systems and reduce the environmental impacts associated with farming activities; however, the environmental benefits have not previously been quantified for reporting at the national scale. With the 2002 Farm Bill came the requirement that USDA−NRCS assess the environmental effects of the Farm Bill sponsored programs. Subsequently, the Conservation Effects Assessment Project (CEAP) was developed. NRCS and ARS are working together, in collaboration with other federal agencies and universities, to implement CEAP. CEAP consists of two main components: the national assessment and the watershed assessment studies (Mausbach and Dedrick, 2004). The purpose of the national assessment is to estimate the environmental benefits obtained from USDA conservation programs at the national level. The purpose of the watershed assessment studies component of CEAP is to complement the national assessment by providing more in−depth assessment of water quality and other benefits at a finer scale of resolution than is possible at the national level.

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CEAP is an on−going mix of data collection, model development, model application, and analyses of results. Computer modeling is an essential part of this assessment since it is not possible to monitor the numerous conditions where the conservation practices are implemented. The national assessment involves field−level modeling and watershed−level modeling. Field−level modeling will be conducted for each of the National Resources Inventory (NRI) sample points comprising the CEAP sample using Agricultural Policy / Environmental eXtender (APEX) (Williams et al., 2000). Offsite estimates will be conducted at the 8−digit watershed scale using a combination of models and databases named Hydrologic Unit Modeling for the United States (HUMUS) (Srinivasan et al., 1993, 1998). HUMUS includes databases on land use and sources of nonpoint and point source pollutants used with the Soil and Water Assessment Tool (SWAT) (Neitsch et al., 2002) to assess water quantity and water quality issues. APEX is used for cultivated cropland because of its strength in simulating agricultural management systems. Outputs from the APEX model are aggregated at the 8−digit watershed level in HUMUS/SWAT. HUMUS/SWAT simulates the hydrology and water quality for non−agricultural land uses and the transport of flow, sediment, nutrients, and pesticides from the land to the outlet of each of the 8−digit watersheds and routes the flow downstream to the next water body. Results will be used to provide national and regional estimates.

An extremely important component of the assessment is the required calibration and validation of the chosen environmental effects simulation models. The need for sensitivity analysis to identify the influential parameters for model calibration is universally acknowledged. Sensitivity analysis is also a prerequisite for model building (Crosetto et al., 2000) and is potentially useful in the model development

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stage as a quality assurance tool to ensure that the assumed dependence of model output on the model input parameters makes physical sense.

This article focuses on the sensitivity analysis of the APEX modeling aspect for the CEAP national assessment. The scale of this study limits individual analysis for each individual location and management condition. The objective of this study was to identify the influential parameters of the APEX model by applying an efficient sensitivity analysis method to representative sets of APEX model data from across the U.S. Therefore, the model calibration procedure can focus on those influential parameters while fixing those non-influential model parameters. The variance-based sensitivity analysis and the Morris method and its enhanced version are briefly described in this study. A case study, randomly selected from the representative sets of APEX model data, was conducted to compare the rankings based on variance-based measures and the rankings based on enhanced Morris measures. The more efficient enhanced Morris method was then chosen for sensitivity analysis for the national assessment.

Materials and Methods

APEX

APEX was developed as an extension of the Environmental Policy Impact Calculator (EPIC) model (Williams, 1990; Williams and Sharpley, 1989) to enable simulation of large complex farming systems in whole farm and small watershed management. APEX tracks water, nutrients, pesticides, carbon, and soil erosion on a daily basis as functions of daily weather data, soil characteristics, and agricultural management practices such as planting, tillage, and nutrient applications.

Water movement, soil chemistry, and crop growth are interrelated. The hydrology component simulates runoff, infiltration, percolation, lateral subsurface flow, evaporation, and snow melt. Several methods can be used to estimate runoff, peak flow, and potential evapotranspiration. The selected methods for the CEAP study are listed in table 1. APEX simulates soil erosion caused by wind and water. Sheet and rill erosion result from runoff, rainfall, snow melt, and irrigation. Seven alternative prediction equations, which are variations of the Universal Soil Loss Equation (USLE), may be used to estimate erosion and sedimentation. The user specifies one as the driving equation. For the CEAP study, MUST was selected (table 1) as the driving equation, although estimated outputs according to RUSLE and MUSLE are also produced.

Wind erosion is estimated using the Wind Erosion Continuous Simulation (WECS) method, which requires the daily distribution of wind speed to take advantage of the mechanistic erosion equation. The approach estimates potential wind erosion for a smooth bare soil by integrating the erosion equation through a day using the wind speed distribution. Then potential erosion is adjusted using four factors based on soil properties, surface roughness, cover, and distance across the field in the wind direction.

Table 1. Selected methods for the CEAP study.

Component	Method
Runoff	NRCS curve number method
Peak flow	Modified rational method
Potential evapotranspiration	Hargreaves method
Erosion/sedimentation	MUST
Curve number	Variable daily (Soil moisture index)

Nutrient cycles are simulated for both the organic and mineral fractions of nitrogen (N) and phosphorus (P). The fractions are subdivided into pools. The nutrient additions and losses and the transformations between the different pools are calculated on a daily time-step through a series of coupled equations that are solved within a mass balance framework.

Plant development is simulated on a time scale based on heat unit accumulation. Potential growth, a function of intercepted solar radiation, is constrained by the most limiting stress (water, N, P, temperature, aeration). All farming operations that take place on the field throughout the year are taken into account. Annual crop growth occurs from planting date to maturity. The effects of weather, soil water content, and bulk density on soil temperature are computed daily for each soil layer. The soil is modeled as a series of horizontal layers through which water and dissolved materials move and through which plant roots penetrate. The tillage practice effects are simulated by incorporating nutrients and crop residues within the plow depth, changing soil bulk density, and converting standing residue to flat residue. Detailed descriptions of the mathematic relationships used to simulate the processes can be found in Williams and Izaurralde (2006).

Database for APEX Sensitivity Analysis

The APEX model requires inputs of daily weather, soil, field management, and site information. Model parameters in the APEX database include the parameters for crops, fertilizers, tillage operations, and pesticides. There is also a parameter file, which contains many equation coefficients, definitions of s-curve, and miscellaneous parameters used in APEX. Representative sets of data (locations shown in fig. 1) from across the U.S. were selected from the domain for the National Nutrient Loss and Soil Carbon database (Potter et al., 2006), which were upgraded to APEX model input formats. These APEX model runs (continuous simulation of 1960-2001) were selected to represent the variation in climate, irrigation, soil texture group (fine, moderately fine, medium, moderately coarse, coarse, organic), major crops (currently only soybeans, corn, and winter wheat are included), and tillage system (conventional, mulch, and no-till) (table 2).

The average annual precipitation for these selected locations is from 238 to 1493 mm. Figure 2 shows the frequency distribution of the average annual precipitation. The average monthly maximum temperature is from -10°C to 40°C, and the average monthly minimum temperature is from -21°C to 23°C for these selected locations (fig. 3).

Parameters Considered for Sensitivity Analysis

APEX contains a large number of inputs and model parameters. Ideally, all parameters should be screened to determine relative importance. However, this would result in a large number of simulations considering the magnitude of this study. The parsimony principle (Trocine and Malone, 2000) states that only a few parameters are responsible for most of the variability of model outputs, while most other parameters contribute little. Therefore, the sensitivity analy-

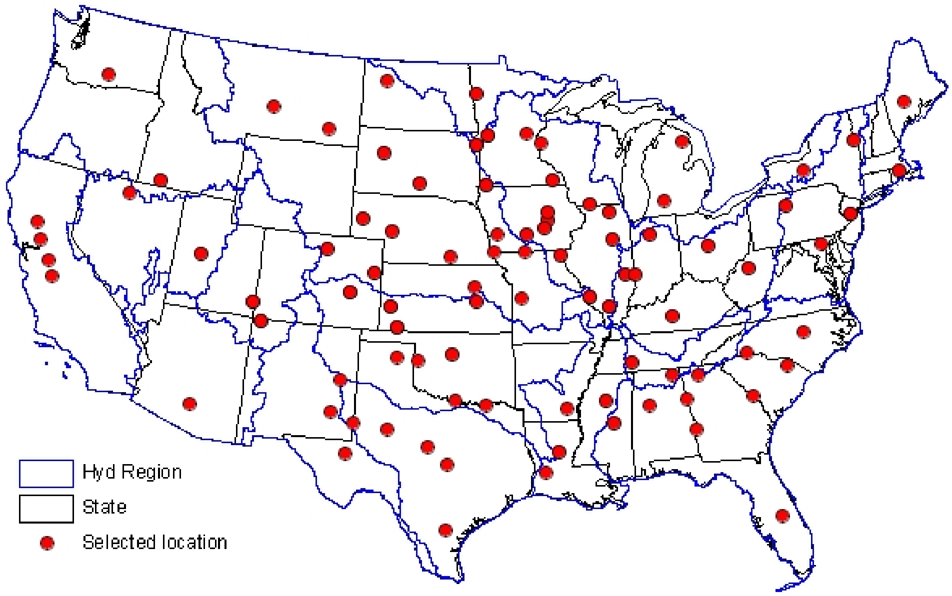

Figure 1. Locations of the selected APEX model dataset.

Table 2. Representing soils, crops, and tillage included in the study.

Representative Type	No.	Total No.
Soil texture group		
Coarse	25	159
Fine	28	
Medium	64	
Moderately coarse	18	
Moderately fine	22	
Organic	2	
Hydrologic group		
A	18	159
B	75	
C	37	
D	29	
Crop		
Soybeans	40	159
Corn	66	
Winter wheat	53	
Tillage		
Mulch	23	159
Conventional	118	
No-till	18	

sis performed in this study was restricted to 15 parameters (table 3), which were selected by experience and believed to be potentially important parameters governing the major processes represented by APEX. The ranges of the 15 selected parameters were based partly on the values recommended for APEX in the model documentation (Williams et al., 2003) and partly on expert knowledge and experience.

The root growth-soil strength parameter (RGSS) sets the soil strength constraint on root growth. The root growth stress decreases with the increase of RGSS. The soil water lower limit in the top 0.5 m of soil (SWLL) is a fraction of wilting point. The N fixation (NFIX) limits N fixation estimates based on soil water, nitrate content, crop growth stage, or crop N uptake demand. The soluble P runoff coefficient (SPRC) is the P concentration in the sediment divided by that of the water. Biological mixing occurs at the end of each year at an efficiency set by BMEF and a maximum depth set by BMMD. HPETE is the air temperature difference exponent in the modified Hargreaves method (Hargreaves and Samani, 1985; Williams and Izaurralde, 2006). PET increases with the increase of HPETE. The NRCS curve number index coefficient (CNIC) drives the NRCS curve number (USDA, 1972) retention parameter as a function of precipitation, PET, and the maximum retention parameter. Higher values of CNIC increase runoff and the corresponding sediment losses, and vice versa. The effect of crop residue on the RUSLE C factor is governed by the exponential coefficient (RCFC). The exponential coefficient of tillage effects on residue decay rate (TERD) impacts carbon mineralization.

The potential heat units (PHU) are the number of heat units required for a specific crop to mature at a specific

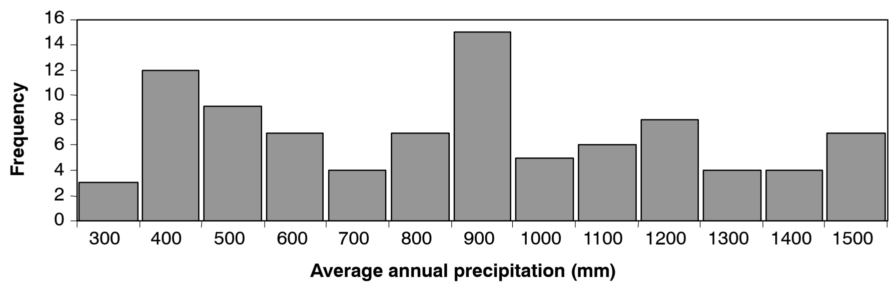

Figure 2. Average annual precipitation (1960-2001) frequency distribution for the selected locations.

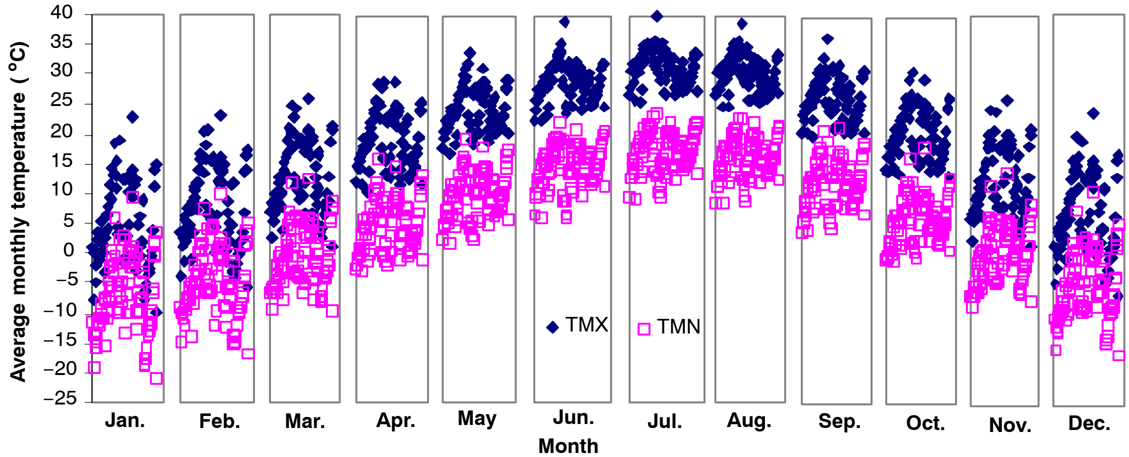

Figure 3. Average monthly maximum (TMX) and minimum (TMN) temperature (1960−2001) for the selected locations.

location. The heat units are accumulated degrees of temperature (Celsius) between the day's mean temperature and the crop's minimum growth temperature. The fraction of humus in the passive carbon pool (FHP) partitions the carbon in the humus between the passive and slow pools. The daily wind speed distribution is simulated using the modified exponential equation (Williams and Izaurralde, 2006), where the power parameter (UXP) adjusts the exponential distribution of wind speed. The groundwater storage is subject to deep percolation from the system and return flow (to channel). The return flow ratio (RFP) sets the return flow portion.

Sensitivity Analysis

The effects of the parameters listed in table 3 were assessed for APEX model outputs of runoff (Q), water yield (WYD) (including surface runoff, lateral subsurface flow, and return flow from groundwater, which contribute to streamflow), soil loss by water (SED), soil loss by wind (YWDN), soluble P loss in runoff (QP), soluble N loss in runoff (QN), particulate P loss (YP), particulate N loss (YN), soil organic carbon change (WOC), and crop grain yield (YLD). These APEX outputs are of considerable interest to the national assessment. It is essential for the sensitivity analysis to determine which parameters most influence these outputs by ranking their importance. In this study, the ranking 1st to 4th parameters were regarded as influential, and parameters ranking below 10th were regarded as non−influential.

Parameter Overall Influence

Model parameters interact within the linked system of equations of the model to produce the simulation outputs. The overall influence of a parameter is the sum of all effects involving that parameter, including both the main effect and the interaction effects. The main effect of an input parameter is the effect that is additive on the output and independent of the values that the other parameters may take. An input parameter has interaction effects if its effect on the output depends on the values that the other parameters may take. For instance, in the model of bulk density change in the plow layer (Williams, 1995):

$$BDP = BDP_o - (BDP_o - \frac{2}{3} BD_o)(EF) \qquad (1)$$

where BDP is the bulk density in soil layer P after tillage, BDP_o is the bulk density in soil layer P before tillage, BD_o is the bulk density of the soil when it has completely settled after tillage, and EF is the mixing efficiency of the tillage operation. The main effect of BDP_o is the first term BDP_o because its effect on the model output is additive and independent of the values of the other parameters. The interaction

Table 3. APEX input parameters and their ranges considered in sensitivity analysis.

Input File	Parameter (Abbreviation)	Description	Lower Range	Upper Range
PARM	parm2 (RGSS)	Root growth soil strength	1	2
	parm5 (SWLL)	Soil water lower limit in the top 0.5 m soil depth	0.3	0.7
	parm7 (NFIX)	N fixation	0	1
	parm8 (SPRC)	Soluble P runoff coefficient	10	20
	parm11 (MFSG)	Moisture fraction required for seed germination	0.4	0.7
	parm29 (BMEF)	Biological mixing efficiency	0.1	0.5
	parm31 (BMMD)	Maximum depth for biological mixing (m)	0.1	0.3
	parm34 (HPETE)	Hargreaves PET equation exponent	0.5	0.6
	parm42 (CNIC)	NRCS curve number index coefficient	0.5	5
	parm46 (RCFC)	RUSLE C factor coefficient	0.5	5
	parm52 (TERD)	Exponential coefficient of tillage effect on residue decay rate	5	15
OPS	PHU	Potential heat units (°C)	800	2400
SOIL	FHP	Fraction of humus in passive pool	0.3	0.9
APEXCONT	UXP	Power parameter of modified exponential distribution of wind speed	0.1	0.6
	RFP	Return flow ratio	0.4	0.95

effect of BDP_O with EF is given by the term $(BDP_O)(EF)$ because the effects of BDP_O and EF both depend on the value the other parameter may take.

The number of interaction terms usually grows with the number of parameters and with the range of variation of the parameters (Saltelli et al., 2000a). The overall influence is the appropriate measure in identifying those parameters that have a significant impact on model output either as a main effect or an interaction effect.

Variance−Based Sensitivity Analysis

Variance−based sensitivity analysis estimates the fractional contribution of each parameter to the total variance of the model output (Archer et al., 1997; Saltelli et al., 2000b). The extended Fourier amplitude sensitivity test (FAST) method (Saltelli et al., 1999) and the method of Sobol (Sobol, 1993; Homma and Saltelli, 1996) are capable of estimating the total sensitivity index, defined as the sum of all effects involving the parameter. The extended FAST was used by Wang et al. (2005a) for EPIC and by Wang et al. (2005b) for DRAINMOD−N II (Youssef et al., 2005). Description of the extended FAST sampling procedure and the computational details can be found in Saltelli et al. (1999, 2000a, 2000b) and Schwieger (2004). The core feature of the sampling is based on Fourier transformation of multidimensional input factors into a frequency domain, which constructs a search curve that scans the entire input space (Saltelli et al., 2000b). In this study the extended FAST sampling and FAST total sensitivity index computation were performed using the public domain tool SIMLAB (Joint Research Centre, 2003). FORTRAN code was developed to automatically update APEX input files with generated parameters, launch the APEX run, and organize APEX outputs into SIMLAB required format for computing FAST total sensitivity indices.

Variance−based sensitivity analysis is very reliable for analyzing non−linear and non−monotonic hydrological and water quality models (Melching and Yoon, 1996) because it is "model free" in the sense of independence from assumptions of linearity. Furthermore, sensitivity indices are quantitative measures. The main drawback of the variance−based analysis is the computational cost, as it requires a large number of model runs (Campolongo et al., 2005). An alternative to the variance−based sensitivity analysis is the enhanced Morris measure proposed by Campolongo et al. (2005).

Morris Method and Its Enhanced Version

The Morris method (Morris, 1991) calculates the total and interaction effects. The experimental plan proposed by Morris is composed of individually randomized "one factor at a time" (OAT) experiments in which the impact of changing the value of each of the chosen factors is evaluated in turn. For each factor, the OAT in the Morris method starts on selected intervals. The Latin hypercube (LH) sampling technique (McKay et al., 1979) is used to generate the starting points for OAT. LH sampling is a stratified sampling technique. It subdivides each factor into r intervals of equal probability. Random values of the factors are generated such that each interval is sampled only once for each factor, resulting in r sets of non−overlapping samples. It can be regarded as a global experiment because the experiment covers the entire space over which the factors may vary. The Morris method is independent of assumptions about the model structure and works for monotonic and non−monotonic (linear or non−linear) models alike. In addition, it has the distinct advantage of a low computational cost. To evaluate the effect of each factor on model output, the number of model executions is $r \times (k + 1)$, where r is the number of intervals and k is the number of factors.

Table 4 shows a hypothesized example. In this case, only three factors are chosen for the sensitivity analysis with the range of each factor subdivided into only two equal intervals. For all factors, the range of interval 1 is 0.0 to 0.5, and the range of interval 2 is 0.5 to 1. For each factor, each interval is sampled only once, resulting in two sets of LH samples. The Δ is a predetermined constant, 0.05, either positive or negative, provided that after the change the value is still within the same interval. In practical applications, the values sampled in [0, 1] are subsequently rescaled to generate the actual non−standardized values for the model input factors, which are then fed into model input files for simulation runs. The Morris method estimates the effect of each input factor on the model output by computing a number of local measures (see table 4 for Morris local measures) at different points in the input space and then taking their average (Morris, 1991; Saltelli et al., 2000b).

In this study each of the 15 parameters in table 3 was subdivided into 10 equal intervals (assuming uniform distribution); therefore, the total number of model evaluation for one scenario was 160. In comparison, the Sobol method requires a number of model evaluations such as $500 \times (k + 2)$, and the extended FAST method requires about $200 \times k$ (sensitivity forum, http://sensitivity−analysis.jrc.cec.eu.int/).

Campolongo et al. (2005) proposed an enhanced version of the Morris measure. The enhanced Morris measure is the mean of the absolute values of Morris local measures. Campolongo et al. (2005) believed that the enhanced Morris measure is better than the traditional Morris mean for ranking factors in order of importance. The reason is that if the Morris local measures contain opposite signs, which occurs when the model is non−monotonic, then some effects may cancel

Table 4. Morris method for three factors, each with two intervals (LH = Latin hypercube sampling, OAT = one factor at a time).

	Factor Set	Standardized Factor Value			Model Output	Morris Local Measure		
		Factor1	Factor2	Factor3		Factor1	Factor2	Factor3
LH 1		x1	x2	x3	y1			
	OAT 1	x1 + Δ	x2	x3	y2	(y2 − y1) / Δ		
	OAT 2	x1 + Δ	x2 + Δ	x3	y3		(y3 − y2) / Δ	
	OAT 3	x1 + Δ	x2 + Δ	x3 + Δ	y4			(y4 − y3) / Δ
LH 2		xx1	xx2	xx3	y5			
	OAT 1	xx1	xx2 + Δ	xx3	y6		(y6 − y5) / Δ	
	OAT 2	xx1 + Δ	xx2 + Δ	xx3	y7	(y7 − y6) / Δ		
	OAT 3	xx1 + Δ	Xx2 + Δ	xx3 + Δ	y8			(y8 − y7) / Δ

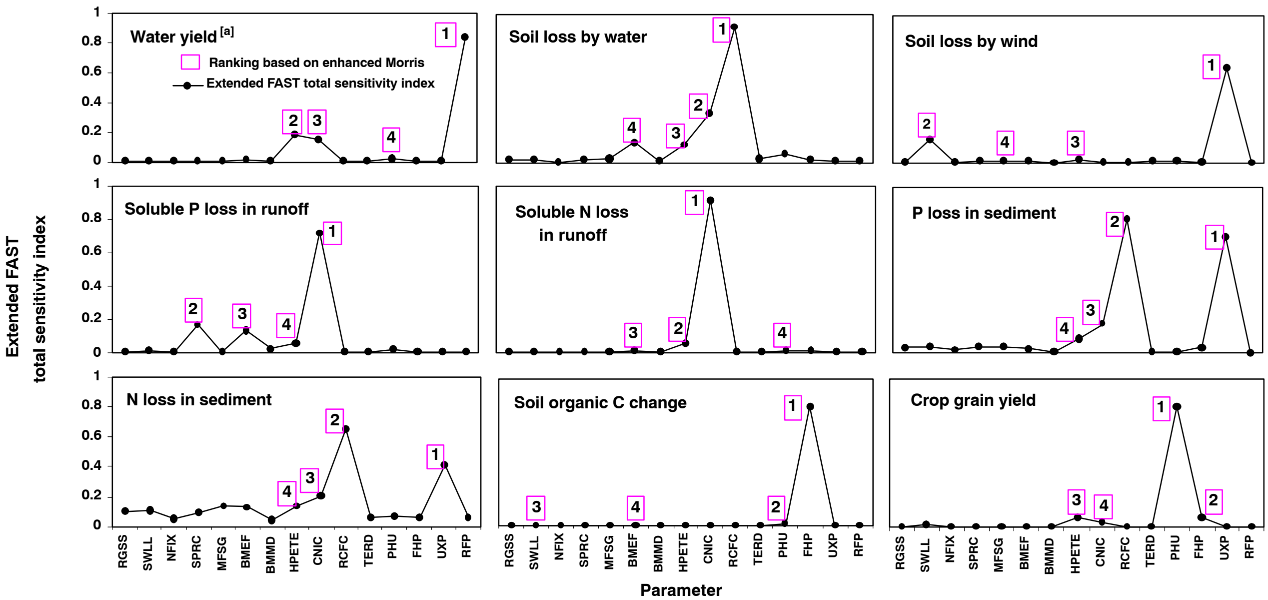

Figure 4. Extended FAST sensitivity indices (N = 2895 simulations) and sensitivity ranking based on enhanced Morris measure (N = 160 simulations). The site is within the Embarras watershed, in Lawrence County, Illinois. [a] Water yield = runoff + return flow + lateral subsurface flow.

each other out when computing the mean. Campolongo et al. (2005) compared the sensitivity rankings based on variance-based measures vs. rankings based on enhanced Morris measures. Their experimental results showed that the enhanced Morris measure has the capability to distinguish between influential and non-influential model parameters at a reduced computational cost.

Case Study to Compare the FAST and the Enhanced Morris Method

A sample data set was randomly selected from the database for APEX sensitivity analysis. It is within the 8-digital watershed 05120112, referred to as the Embarras watershed, in Lawrence County, Illinois (approx. 38° N, 87° W). The soil is Sparta loamy sand, and the crop is winter wheat. The average annual precipitation is 1027 mm. The extended FAST total sensitivity indices for the 15 parameters in table 3 are plotted in figure 4 for different APEX outputs. Figure 4 also shows model parameters ranked 1 to 4 according to enhanced Morris measures. Results confirm that, with just 160 model executions compared to the extended FAST of 2895 model executions, the enhanced Morris measure is capable of identifying the subset of influential parameters.

The influential (ranking 1st to 4th) parameters for each APEX output based on extended FAST and enhanced Morris measure are very similar. The 1st and 2nd rankings were identical for 7 out of 9 of the APEX outputs. For the other two (P loss and N loss in sediment), the 1st and 2nd rankings were reversed. In this test case, six non-influential parameters (RGSS, NFIX, MFSG, BMEF, BMMD, and TERD), which are ranked 10 to 15 based on both extended FAST and enhanced Morris measure, could be fixed, while the other nine parameters are considered for calibration depending on the interest of APEX outputs. For example, if the sole interest is water yield, the model could be calibrated based on RFP, HPETE, and CNIC.For the nine APEX outputs, the enhanced Morris measure never confounds groups of influential and non-influential parameters. This test case, together with the tests reported by Campolongo et al. (2005), confirmed the reliability of the enhanced Morris measure in screening a subset of influential parameters. This is important for the national analysis, where efforts can only focus on the influential parameters for calibration purposes.

Results of Enhanced Morris Method and Discussion

The enhanced Morris sensitivity measure was saved in a Microsoft Access table (MorrisMean). The MorrisMean table includes an ID identifier for each location in figure 1. Because the representative datasets selected for the sensitivity analysis were from the National Nutrient Loss and Soil Carbon database (NNLSC) (Potter et al., 2006), the same ID identifier as in the NNLSC was used in the MorrisMean table, but not renumbered from 1 to 159. The ID is linked with specific site information, daily weather, soil characteristics, field management, and model parameters for crops, fertilizers, tillage operations, pesticides, and others. For the enhanced Morris sensitivity analysis, 160 continuous simulations of 42-year intervals were conducted for each ID with only the parameters listed in table 3 being changed. These parameters were listed as the field names of the resulting table MorrisMean. The enhanced Morris measures for each parameter based on APEX yearly and annual average outputs (except that the soil organic carbon change is only for the simulation period) were recorded. Enhanced Morris measures show that only a few parameters are influential on APEX outputs. Figure 5 plots the Morris measures for influential parameters for runoff (CNIC and HPETE), soil loss by water (CNIC, RCFC, and HPETE), and soil loss by wind (UXP, PHU, and SWLL) as examples. Figure 5 illustrates that sensitivities are dynamic in the temporal dimension, as indicated by Ratto et al. (2001). Changes in sensitivity from year to year occur because climate variables, temperature, and precipitation are model inputs that interact with other model parameters.

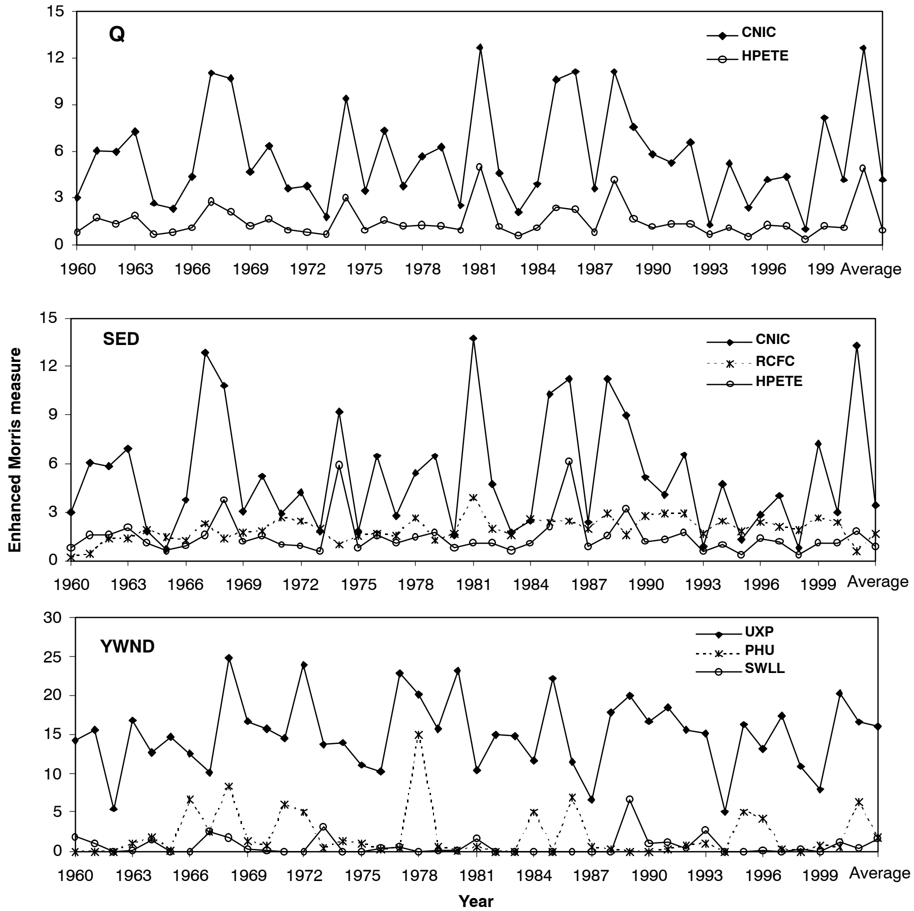

Figure 5. Sensitivities of yearly and annual average outputs to APEX parameters for ID 53631 in the 8-digital watershed 03040201, in Dillon County, South Carolina.

The parameter rankings based on average annual outputs were saved in a Microsoft Access table (RANK) where ID, output, and rank1 to rank15 are field names. There are ten records, each for one of the ten APEX outputs, for each ID. Parameters are listed for each output by importance based on the enhanced Morris measures. Hence, it is convenient to find the influential parameters for different APEX outputs. The RANK and MorrisMean tables can serve as references (ftp.brc.tamus.edu) for other APEX model users in finding influential parameters for similar modeling conditions by simply creating a query of interest. For this national assessment, efforts were focused only on very influential parameters. Therefore, statistical analyses were performed to determine the frequencies with which parameters appeared in 1st and 2nd ranking for each APEX output studied. Thus, the percentage of relative importance of parameters can be calculated. Figure 6 shows the percentage importance of parameters ranked 1st for the ten APEX outputs, with only the percentage greater than 5% and the total percentage for all the other parameters illustrated. CNIC was very influential in simulating runoff (over 90% importance). Correspondingly, its percentage importance is high for other water-related output variables, e.g., over 80% importance for soil loss by water. UXP is exclusively ranked 1st for wind erosion, and FHP is greatest in importance for soil organic carbon change.

Figure 7 shows the percentage importance of the parameters ranked 2nd, with only the percentage superior to 5% and the total percentage for all the other parameters illustrated. HPETE has over 90% importance in the ranked 2nd list for runoff. SPRC has over 85% importance in the ranked 2nd list for P loss in runoff. In general, there are more diverse parameters with over 5% importance ranking 2nd than parameters with over 5% importance ranking 1st for model outputs (see figs. 6 and 7). This is also true for the ranking 3rd parameters (not presented). This indicates that although sensitivities are dynamic, the very influential parameters appear very influential in most cases, whereas the parameters with lower rankings are more diverse. Table 5 summarizes the influential parameters identified for the APEX outputs based on the frequencies (or percent importance) of parameters that appear in the 1st and 2nd ranking. Overall, CNIC is influential for most APEX outputs except for soil loss by wind. Four parameters (HPETE, MFSG, RCFC, and PHU) are influential for more than two APEX outputs studied. Another seven parameters are influential for only one APEX output studied, e.g., UXP and SWLL are influential for wind erosion. In general, by the percentage of relative importance among all the cases in the database, NFIX, BMEF, and BMMD are not influential. The sensitivity analysis was performed for only the 15 parameters in table 3. Other input parameters (e.g., upland slope and initial organic carbon) were not analyzed in this study; however, they may have greater influence than that of these analyzed parameters on APEX outputs.

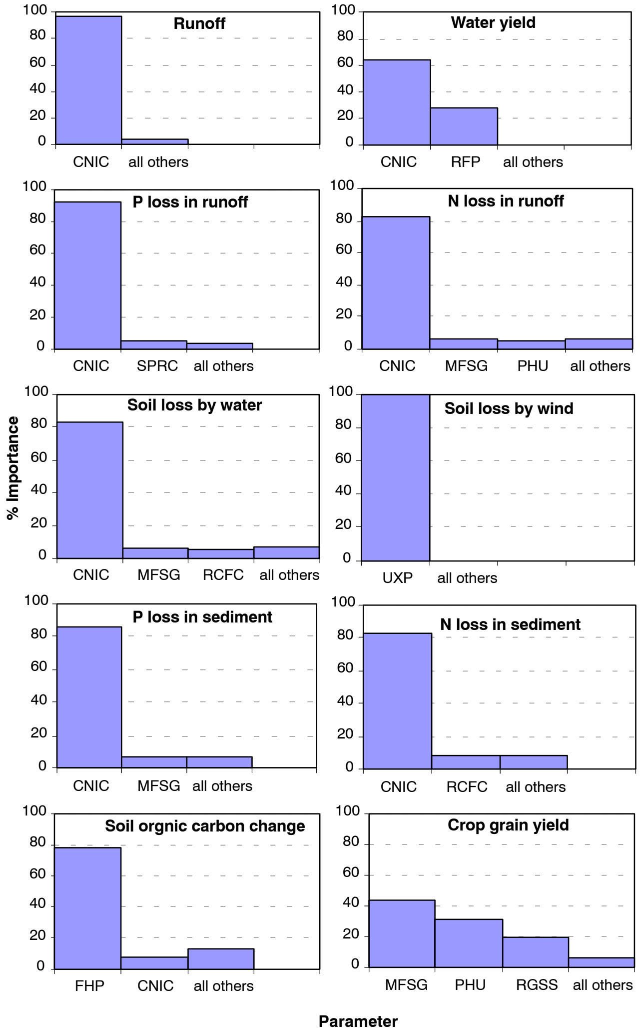

Figure 6. Percentage importance of parameters ranked 1st for APEX outputs, with only the percentage >5% and the total percentage for all the other parameters illustrated. Percentage importance is based the frequencies of parameters appeared in the 1st ranking.

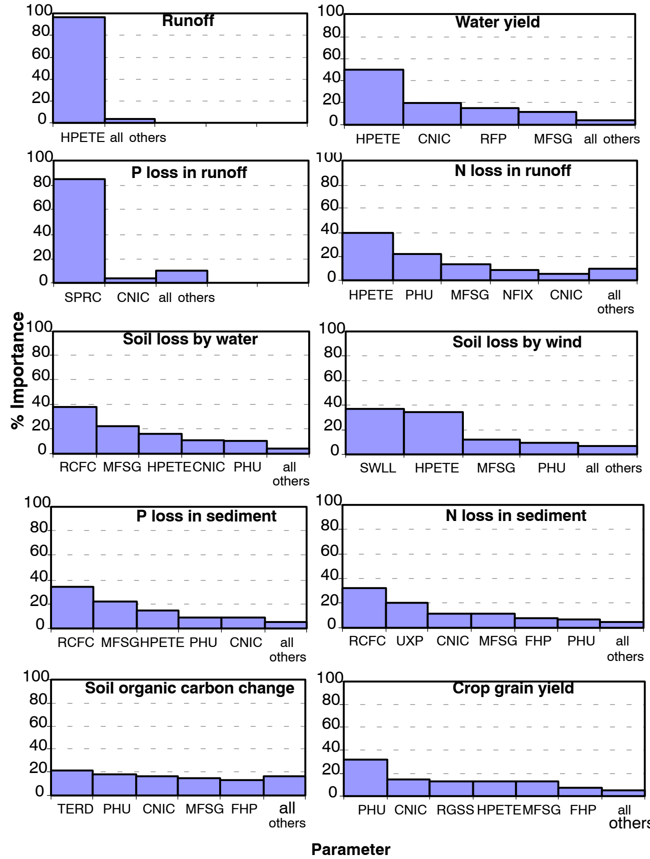

Figure 7. Percentage importance of parameters ranked 2nd for APEX outputs, with only the percentage >5% and the percentage for all the other parameters illustrated. Percentage importance is based on the frequencies of parameters appeared in the 2nd ranking.

CONCLUSIONS

Representative sets of APEX model data from across the U.S. were used for sensitivity analysis to determine influential parameters on APEX outputs of crop grain yields, runoff/water yield, water and wind erosion, nutrient losses in runoff and sediment, and soil carbon change for a national assessment project. Both the variance−based sensitivity analysis (the extended FAST) and the enhanced Morris method were used for a sample case, randomly selected from the APEX database, to test if the enhanced Morris measure is generally comparable with the variance−based total sensitivity index in identifying the influential parameters. The test case confirmed the reliability of the enhanced Morris measure in screening subsets of influential and non−influential parameters. Therefore, for the national assessment, where the cost of applying variance−based techniques would be excessive, the enhanced Morris method was used.

The enhanced Morris measure based on yearly outputs illustrates that sensitivities are dynamic in the temporal dimension, mainly as a result of year−to−year climatic differences. Although sensitivities are dynamic in both

Table 5. Influential parameters (checked) for APEX outputs at the national scale.

Output	CNIC	HPETE	MFSG	RCFC	PHU	UXP	SWLL	SPRC	FHP	RFP	RGSS	TERD
YLD	Yes		Yes		Yes						Yes	
SED	Yes		Yes	Yes								
YWND		Yes				Yes	Yes					
Q	Yes	Yes										
YN	Yes			Yes								
QN	Yes	Yes			Yes							
YP	Yes		Yes	Yes								
QP	Yes							Yes				
WOC	Yes								Yes			Yes
WYD	Yes	Yes								Yes		

temporal and spatial dimensions, the very influential parameters appear very influential in most cases, and the parameters with lower ranking are more diverse. At the national level, the influential parameters were identified for the ten APEX average annual outputs based on the frequencies of parameters appeared in the 1st and 2nd ranking. For crop grain yield, the potential heat units (PHU), root growth soil strength (RGSS), moisture fraction required for seed germination (MFSG), and the NRCS curve number index coefficient (CNIC) are influential. CNIC, RUSLE C factor coefficient (RCFC), and MFSG are influential to soil loss by water. Soil loss by wind is significantly impacted by the power parameter of modified exponential distribution of wind speed (UXP), soil water lower limit of water content in the top 0.5 m soil depth (SWLL), and the Hargreaves PET equation exponent (HPETE). CNIC and HPETE are important to runoff. The fraction of humus in passive pool (FHP) and exponential coefficient of tillage effect on residue decay rate (TERD) are important to soil organic carbon change. CNIC, HPETE, and the return flow ratio (RFP) are influential to water yield. In general, CNIC is influential for most APEX outputs except for soil loss by wind. HPETE, MFSG, RCFC, and PHU are influential for more than two APEX outputs. The sensitivity results were within the limitation that only the 15 parameters in table 3 were considered for the analysis in this study.

The enhanced Morris measures of APEX yearly and annual average outputs to 15 selected APEX parameters were saved in a Microsoft Access table (MorrisMean); the corresponding ranking of parameters based on APEX annual average outputs was saved in another Microsoft Access table (RANK). Both MorrisMean and RANK have ID identifiers linking with specific site information, daily weather file, soil, field management, and other model parameters. Encapsulating the spatial and climatic variability, the RANK and MorrisMean Access tables can serve as references (ftp.brc.tamus.edu) for other APEX model users for similar modeling conditions.

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